AUTOMATED SYNTHETIC HYPERSPECTRAL IMAGE GENERATION FOR CLUTTER COMPLEXITY METRIC DEVELOPMENT

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ABSTRACT

Imaging sensors and automatic target recognition (ATR) algorithms are an integral part of modern combat systems. We present a method to automate the efficient synthesis of hyperspectral images used as aid in the evaluation and development of ATR algorithms. To ensure reliable inferences from these processes, it is required that the different levels of difficulty for ATR performance are adequately represented in the generated images. We employ the Digital Imaging and Remote Sensing Image Generation (DIRSIG) software for the image synthesis, and model each image as a function of the input parameters needed for the image synthesis. The computational complexity of image generation makes gradient-based, and similar adaptive schemes inappropriate for sampling this multidimensional function. We present a progressive adaptive sampling algorithm based on the equalization of the histogram of the already obtained samples. The algorithm requires no prior knowledge of how the images vary with the inputs used in their synthesis, and the computational overhead is minimal. The images generated with the aid of this algorithm are compared to those generated from a combination of random, and even spaced input parameters to DIRSIG. An improvement in diversity with respect to ATR performance is recorded for the images generated using the adaptive sampling algorithm.

1 INTRODUCTION

Synthesized hyperspectral images have been successfully used as aid in the evaluation and development of imaging sensors and related algorithms. Such images have been used in the design stages to pre-evaluate the imaging products from a sensor (Lentilucci et al. 1998), serve as test data for algorithm design either because real data is not available (Arnold et al. 2000; Shi and Healey 2003), or to augment when it is limited (Schott et al. 1997). Our objective is to synthesize hyperspectral images to be used in the development of a clutter complexity metric. Such a metric will be an indication of the intrinsic difficulty for an automatic target recognition (ATR) algorithm to identify a target in an image. It is derived as an aggregation of statistical image features, that correlates best with baseline ATR performance. The feasibility of this approach has been shown in previous work (Fadiran and Kaplan 2004; Fadiran et al. 2006b).

In obtaining the described clutter metric, a training process is employed in deriving the selection and combination of image features that correlate best with a baseline ATR performance. This requires the availability of a statistically representative set of images. The question of representation is two-fold, that of fidelity on a per image basis, and the need for an adequate number of images at the different levels of difficulty for target detection by an ATR. This works addresses the latter.

We employ the Digital Imaging and Remote Sensing Image Generation (DIRSIG) (Schott et al. 1999) software for the image synthesis. Each synthesized image may be seen as a function of the input parameters needed for its generation. Some of these may include time of day, season of year, atmospheric profile between the imaging device and the scene etc. The aim is to sample this multidimensional space, such that there is maximum diversity in the synthesized images with respect to ATR detection performance. There is inadequate prior knowledge of how this performance varies with these input parameters, especially when they are combined. Also, synthesizing these images is generally computationally expensive. As a solution to sampling this function, we present a progressive adaptive sampling algorithm. The algorithm requires no prior knowledge of how the images vary with the inputs used in their synthesis, and the computational overhead is minimal.

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In the next section, we describe the process of image synthesis. We also introduce our adaptive sampling scheme and explain how it aids efficient image generation. Section 3 details our experimental setup, then shows and discusses the results. We conclude by highlighting our findings, and making suggestions for further work.

2 HYPERSPECTRAL IMAGE DATABASE GENERATION

2.1 Image Synthesis Model

The Digital Imaging and Remote Sensing Image Generation (DIRSIG) model has be been used for generating multi- and hyperspectral images in the 0.3 to 20 micron region (Schott et al. 1999). It is an integrated collection of first principle based sub-models that account for scene geometry, atmospheric contributions, illuminating sources, and properties of materials in the imaged scene. After these factors are established, a ray-tracing process is employed in rendering the scene. The process of synthesizing images using DIRSIG is well documented (Digtial Imaging and Remote Sensing Laboratory 2006).

Hyperspectral images are *cubes* of data in which two of the dimensions are spatial, and the third dimension is spectral. The spectral information is particularly useful when there is a limitation on the spatial resolution that can be obtained. Using multi-spectral ATR algorithms, objects in hyperspectral scenes that span less than one pixel can be identified from their spectral signatures. Generally, the approach of multi-spectral ATR algorithms focuses on the spectral rather than the spatial information in the images (Landgrebe 2003).

The spectral signature of a material in a synthesized image depend on the input parameters DIRSIG. The effect that these factors have on the signature also depends on the region of the electromagnetic spectrum that is being considered. Some factors have been determined to cause more significant changes in the regions of the spectral signatures for which we generated images - the visible to near infrared (0.35 - 1.0 nm). Some of these factors are: time of day, range of visibility, atmosphere profile type etc. (Landgrebe 2003). A further constraint is imposed on our choice of factors by the adaptive sampling algorithm that we use as aid in the image synthesis process: their values must be monotonically increasing or decreasing in magnitude. This requirement will be explained in the subsection that describes the adaptive sampling scheme. We identified three of these factors to form a 3-dimensional space as described in the introduction. Each generated image is then a result of the combination of these factors as inputs to the DIRSIG model. These factors and the ranges in the dimensions that they represent are:

- Minute of day (1-1440 minutes)
- Day of year (day 1-365)
- Visibility parameter (0-40km)

While our choice of factors for this work is based on experience with generating these types of images, this framework can also be used for identifying the significance of other factors and their ranges. The emphasis in this work is the establishment of the framework in which the adaptive sampling is used as aid in the image generation process.

2.2 Efficient Image Database Generation

The computational complexity of image generation makes gradient-based, and similar adaptive schemes inappropriate for sampling the described multidimensional function. This is because the number of generated samples usually has to be kept at a minimum. There is a need for an adaptive sampling scheme that is able to efficiently sample the function with no prior knowledge of how the function changes with the independent variables it depends on, in this case, the image synthesis input parameters. Such a scheme should also be able to achieve this with minimal computational overhead. As a solution, we have developed an adaptive scheme that fulfils these requirements, namely, the Adaptive Sampling by Histogram Equalization (ASHE) (Fadiran et al. 2006a) algorithm. This is a progressive adaptive sampling scheme in which the subsequent sample locations are determined based on the state of the distribution of an objective value associated with the function in question. We have shown that progressively sampling to achieve a uniform distribution in the objective function value, results in the efficient distribution of samples. That is, a higher density of sample points in regions of relatively higher complexity in a function.

The objective function value associated with each image was determined by the performance of an idealized ATR, this served as our baseline. The function value at any sampled point was represented as the false alarm rate at an arbitrarily set threshold. The same threshold was used throughout the work.

Simulated active walkers (Helbing et al. 1997) are employed as samplers, and their steps at each stage of the process is determined by the state of the distribution of already collected function values. Their locations in the space are the sampled points. Obtaining a distribution of the already sampled function values at each stage is the only computational overhead incurred.

The described algorithm has been shown to achieve two purposes that are apparently equivalent: efficient distribution of sample points by avoiding regions of relatively

lower complexity, and improving diversity in distribution of sampled function values.

The listing in Algorithm 1 shows how the ASHE algorithm aids the efficient generation of hyperspectral images.

Multiple active walkers are employed in the process to ensure that there is an initial even spread of the starting sample locations. There is however a needed trade-off between the required initial spread of samples and the number of steps that is taken by each walker. Obviously, the greater the number of steps that can be taken, the more the distribution will tend towards the uniform. Sampling with a single walker to maximize the number of steps may result in the walker remaining in a local region of the function. Since in this case the state of the distribution will only be dependent on local function values, the algorithm only attempts to obtain a uniform distribution of the values in this sub-domain. The use of multiple walkers ensures that the state of the distribution is based on function values in the whole domain. For this work, 5 active walkers were employed to obtain $n = 125$ samples, each walker taking $(n - 5)/5 = 24$ steps in the process.

The short, and long steps are defined as functions of the size of the space being sampled. Thus, the short step $= \alpha \times N$, and long step $= \beta \times N$, where α and β have been determined empirically to be 0.04 and $\geq$ 0.3 respectively. N in this case is a 3-element vector, with elements equal to the lengths of each of the dimensions that make up the space. The algorithm is less sensitive to changes in β, since any value ≥ 0.3 results in a movement away from the vicinity of the original location.

Changes in the state of the distribution of the function values determine whether a long or short step is taken by a walker. These changes were computed as the mean squared error between the distribution, and a uniform distribution with the same number of bins. This value tends towards 0 as the distribution moves towards the uniform. Thus, if a sample addition to the distribution causes a reduction in the error, a short step is taken by the walker that obtained the sample, a long step is taken otherwise.

Note that, since there has to be a correlation between the step sizes of the active walkers in the input parameters space, and their sample contribution to the distribution. It is thus required that the input parameters be monotonically increasing or decreasing. Otherwise, the step sizes become of no effect, and their movement will be essentially random.

A self-avoidance mechanism (Rodnick and Gaspari 2004) is implemented to ensure that no location is sampled multiple times. A marker is placed on every previously sampled location, and a walker that falls into this location moves to another *close* sample location. In this case, the walker moves in unit step sizes in all dimensions, in a random direction, until a location that has not being sampled is reached.

3 EXPERIMENTS

We generate hyperspectral images according to the urban scene from the DIRSIG tutorial (Digtial Imaging and Remote Sensing Laboratory 2006) by varying the three factors identified in Subsection 2.1. One band from this imaged scene is shown in Figure 1.

Figure 1: A single band ($\lambda = 0.56$ nm) from the hyperspectral image of the urban scene. The spatial size is 128×128 pixels. The arrow indicates the region cropped as target.

We generate different images from this scene by keeping other input parameters constant while varying the three input parameters that make up the multi-dimensional space. The arguments to DIRSIG are contained in a series of parameter files. These files contain the values of the factors that determine the nature of the synthesized images amongst other information. The 3-dimensional coordinates of an active walker are written into the appropriate parameter files that serve as input to DIRSIG. The algorithm is implemented with a MATLAB script.

Algorithm 1 Synthesizing hyperspectral images using the ASHE algorithm

Initial definitions:
objective function - False Alarm Count (FAC)
factors that the Objective function is dependent on - 3 identified in Section 2.1
range and possible values that these factors can take - also listed in ” ”

Sampling initialization:
obtain initial random locations in 3-dimensional space using active walkers
synthesize images for combination of factors from these locations
compute FAC from initial sample image points
compute normalized histogram from initial sample FAC values

while no. of synthesized images $\leq$ required no. of images **do**
  for all active walkers **do**
    obtain new sample point in multi-dimensional space
      if location has already been sampled
        obtain different but ’close’ sample point
      end if
    synthesize new image based on active walker position
      (*arguments to DIRSIG are coordinates of active walker position*)
    add new image sample from active walker to existing images
    compute FAC for new image addition
    compute new normalized histogram of FAC values after single addition, and
      compare to previous histogram
      if histogram tends to normalized uniform distribution
        single walker takes short† step size in random direction
      else single walker takes long‡ step size in random direction
      end if
  end for
    compute new overall normalized histogram
end while

The values of the † - short, and ‡ - long step sizes are functions of the size of the space being sampled.

We synthesize a set of images using a random combination of these parameters, and another set using combinations of factors that are evenly spaced within their possible ranges. We compare these to the set of images generated by the set of factors determined by the adaptive sampling algorithm. Each of the sets consists of 125 images, 128×128pixels, and 44 equally spaced spectral bands spanning 0.35-1.0nm. Each image takes about 26 minutes to synthesize on a Pentium IV Linux PC with a 3.2GHz processor.

In order to establish a baseline ATR performance, we implemented a normalized, multi-spectral matched filter ATR via the Adaptive Coherence Estimator (ACE). This ATR is idealized, as it uses a spectral signature of a target in question as a template. The resulting ACE statistic is bounded between 0 and 1 and is described in (1), in which $\mathbf{s} \in \Re^L$ and $\mathbf{x} \in \Re^L$ are the target template and pixel under test respectively, and L is the number of bands in the hyperspectral image. The vectors $\mathbf{s}$ and $\mathbf{x}$ may also be composed of multiple pixels in the spatial dimension. In this case, 2-dimensional averages of the target and test pixels are taken in the spatial dimensions to obtain column vectors of the previously stated lengths. $\mathbf{\hat{R}_b}$, with dimensions $L \times L$ is an estimate of the covariance matrix of the background (Li and Michels 2004). The false alarm count at an arbitrary, but constant threshold serves as a measure of our ATR baseline performance. This is the objective function value associated with each synthesized image.

$$\mathbf{ACE_{statistic}} = \frac{|\mathbf{s^T \hat{R}_b^{-1} x}|^{\mathbf{2}}}{(\mathbf{s^T \hat{R}_b^{-1} s})(\mathbf{x^T \hat{R}_b^{-1} x})} \qquad (1)$$

As the image generation process progresses, the baseline ATR performance of the existing images is computed, and the ASHE algorithm attempts to equalize the histogram

of these values. It does this by moving the active walkers away from regions that will result in the generation of images with false alarm values that already have adequate representation, to regions that will result in images that have lower or no representation.

The false alarm count (FAC) is also computed for the sets of images synthesized by a random combination of these factors, and those synthesized using combinations of factors that are evenly spaced within their possible ranges. These image sets are then compared to the adaptively synthesized images on the basis of representation across the range of FAC values. This is determined as the range between the minimum, no false alarm count, to the maximum of all FAC values recorded from the three methods used for image synthesis. By representation, we refer to each bin having at least one image so that an ATR algorithm test on the database would have considered all levels of difficulty. The images are also considered based on the distribution among the different levels of difficulty. That is, a measure of the uniformity in the distribution of images across the different levels of difficulty so that ATR algorithm tests are not biased by over-representation in a particular category of difficulty.

Figure 2 shows the spread of representation over the defined FAC value range, and the levels of representation for each FAC value. There are 106 possible FAC values in the range. As shown by the count of the number of bins with at least 1 image representation, the image set generated using the adaptive algorithm show representation of more FAC values than the other two methods. Note that, none of the methods produce images that have FAC values between 0 and 33. This is due to the threshold value used to determine the false alarm rate for the images. A higher value will result in lower FAC values for all three methods.

A comparison of the normalized versions of these histograms to a normalized uniform distribution with the same number of bins, shows that there is a more even distribution of the FAC values from the image set obtained using the ASHE algorithm. As an objective measure of this, we compute the mean squared deviation of the histograms from a normalized uniform distribution with the same number of histogram bins.

4 CONCLUSION

Our main objective is to synthesize hyperspectral images that are diverse with respect to ATR performance. We identify factors that contribute to variations in hyperspectral images, and model a synthesized image as a function in a multi-dimensional parameter space. Without prior knowledge of how images vary with change in these factors, the typical approaches are either to synthesize images using a random combination of these factors, or using a combination of factors that are evenly spaced within their possible ranges. These methods are not efficient if there are regions in the parameter space that cause more variations in the resulting image than others. Rather, regions of change need to be sampled more densely. On the other hand, the computational expense of synthesizing images is prohibitive for gradient based adaptive sampling algorithms. In order to efficiently sample this space to generate images that are diverse with respect to ATR performance, we sample the space using an Adaptive Sampling algorithm based on Histogram Equalization (ASHE). The algorithm directs the image synthesis process, such that there is a spread of representation in the values that are indicative of ATR performance. Images synthesized using the ASHE algorithm performed better than those synthesized using a random combination of factors, and those generated using a combination of factors that are evenly spaced within their possible ranges when compared on the basis of spread and equality of representation within the ranges of values indicative of ATR performance.

We are currently experimenting with other models to achieve histogram equalization. We also continue the development and use of the ASHE algorithm to identify parameters, and combinations of them that are most significant for variation in images. In general, this scheme can be used for any kind of synthesized data sets to ensure diversity or completeness in representation.

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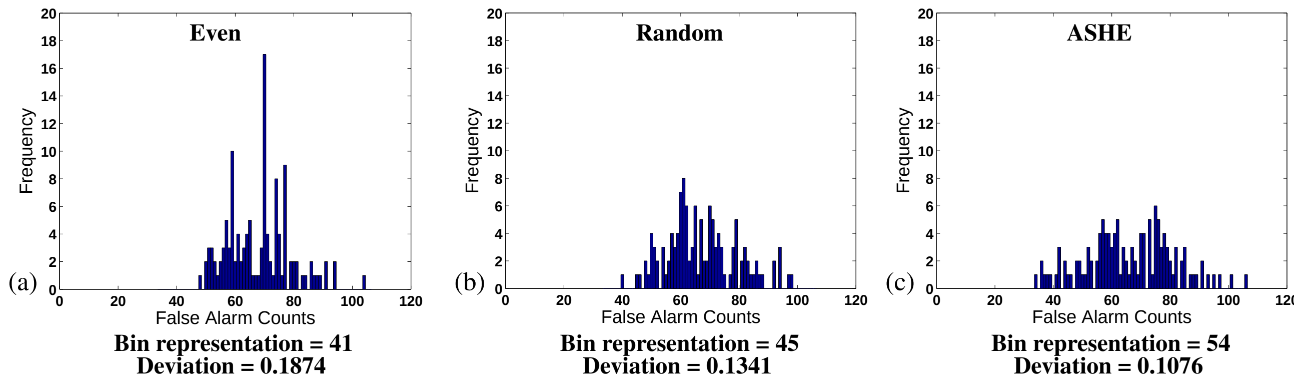

Figure 2: Histograms showing image representation for each of the False Alarm counts. The charts in Figures 2 (a), (b), and (c) show the representation for images obtained from combinations of evenly spaced factors, random combination of factors, and images synthesized based on the adaptive sampling algorithm respectively. The bin representation is the count of bins that have at least one image, there are 106 bins in all. The Deviation values are the mean squared deviation of the histograms from a normalized uniform distribution with the same number of histogram bins.

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